Smart Sensing System for the Detection of Specific Human Motion Symptoms of the Parkinson's Disease

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Abstract: We propose two different wearable wireless sensing systems based on Inertial Measurement Units for the home monitoring of specific symptoms of the Parkinson's disease. In one configuration just one sensor is inserted in a headset, in the other configuration two sensors are positioned on the patient's shins. They recognize and classify noticeable motion disorders potentially dangerous for patients and give an audio feedback. The systems use dedicated algorithms for real time processing of the raw signals from accelerometers and gyroscopes, one of which is based on an artificial neural network and another on a time-based analysis. The headset system detects satisfactorily a wide class of motion irregularities including the trunk disorders, but is poorly reliable on Parkinson's patients. The other system with sensors on the shins provides an early detection of the freezing of gait with excellent performance in terms of sensitivity and precision, and timely provides a rhythmic auditory stimulation to the patient for releasing the involuntary block state.

1 INTRODUCTION

A wide variety of movement disorders and gait irregularities are typical symptoms of the Parkinson Disease (PD) (Nieuwboer et al., 2001). Among others, the freezing of gait (FOG) is a really disabling one. FOG is paroxysmal block of movements, which takes place in an advanced stage of the PD if the patient is not properly covered by the therapy. During the FOG, patients refer that their feet are "stuck to the ground" (Spildooren et al, 2010). In this situation, the patients make attempts to make a step, oscillating and thrusting forward the trunk, which can cause catastrophic events as falls (Bloem et al, 2004). Often, the FOG is anticipated by a progressive step shortening (pre-freezing state) (J. Spildooren et al., 2010), after which the patient stops completely. It has been shown that a rhythmic auditory stimulation (RAS) can lead the patients out of the FOG state (P. Arias and Cudeiro, 2010). The possibility to provide a RAS timely at the onset of the symptom or in the pre-freezing state would avoid the undesired consequences of the block. During the last few years, several different systems for the automatic detection of the FOG have been proposed. These are based on the classification of electrical signals coming from inertial sensors properly positioned on the patient body (Lorenzi et al., 2015), (Mazilu et al., 2014), (Bachlin et al., 2010), (Moore et al., 2013), (B. Sijobert et al., 2014), (Mazilu et al., 2013) (Cola et al., 2015), (Atallah et al., 2014). In our work, we propose the realization of two types of wearable wireless sensing systems based on MEMS accelerometers and gyroscopes, able to recognize in real time specific kinetic features associated to motion disorders typical of (but not limited to) the PD and eventually give an auditory stimulation to the patient to release the involuntary block. They have been designed to be used at home or outdoor, during the daily patient life. One system has the sensor in a headset and uses an artificial neural network (ANN) for the recognition of the motion features as regular steps, short steps, gait blocks, trunk oscillations. Another headset system recently proposed in

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literature (L. Atallah et al., 2014) uses only accelerometers just to detect the gait asymmetries without making any recognition of specific gait features (which is the topic of our system). The other system proposed here has two sensors on the shins and uses a time-based algorithm for the recognition.

Compared to other systems, the headset has the advantage that it is composed by a single sensor integrated in the headphone. This makes the system compact and energy efficient since no wired/wireless connection is required to give the audio-feedback. On the other hand, the headset has the disadvantage that the neck joint mixes signals from the amount of postural problems and irregular movements typical of the Parkinson disease, which makes the detected traces extremely "noisy" and confused (as experimentally proved).

The second system proposed here requires an additional device for the audio feedback, but the two sensors on the shins guarantee the best performance presented in literature to date in terms of sensitivity, specificity, precision and accuracy. It has been tested on a population of PD patients with excellent results.

The board used in the two systems is a prototype called neMEMSi (D.Comotti et al., 2014) whose size is 25x30x4 mm3 (with battery, see Fig. 1a).

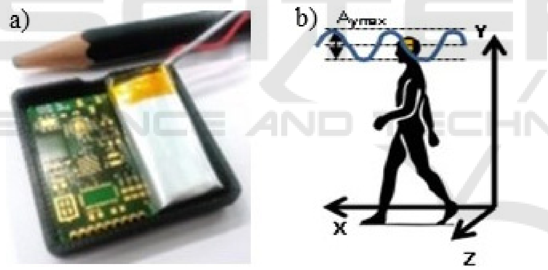

Figure 1: a) A picture of the NeMEMSi board. b) sketch of the reference framework of the headset sensor.

The sensor unit LSM9DS0 integrates a ±16 g (g-force) 3D accelerometer, a ±12 Gauss 3D magnetometer and a ±2000 dps 3D gyroscope. Bluetooth communication is supported. The board integrates an ultralow-power 32 bit microcontroller (MCU) by STMicroelectronics (STM32L1) with 33.3 DMIPS peak computation capability and very low power consumption (down to 233 uA/MHz), Flash memory 256 KB, SRAM 16 KB, EEPROM 4 KB. Thanks to the Cortex™ M3 architecture and the 32 MHz clock frequency, this MCU is optimized for advanced and low-power embedded computations. Actually, until now we performed the measurements on patients using an external station (a pc) for the calculations, since the porting on board requires disclosure of the MCU firmware. However, we are fully confident that the excellent capabilities of the MCU guarantee the same system performance since they are redundant respect to the system requirements. In fact, the same algorithms have been already implemented in an Arduino platform (16 bit MCU ATmega 328P, Flash memory 32KB, SRAM 2KB, EEPROM 1KB, Clock Speed 16MHz, MIPS 16) which is largely less performing of the STM32L1.

2 THE HEADSET SENSING SYSTEM

2.1 The Soft Operation with an Artificial Neural Network

This system is composed of a single sensor inserted in a headset. The reference framework is depicted in Fig. 1b. The y-axis represents the vertical direction, the x-axis represents the direction of the walk. The acceleration along the x direction (Ax, blue) and along the y direction (Ay, red) in the two states are drawn in Fig.2. During the walk, the two accelerations have an oscillatory behaviour, in the stop state Ay is around 10 m/s^2 and Ax is around 0.

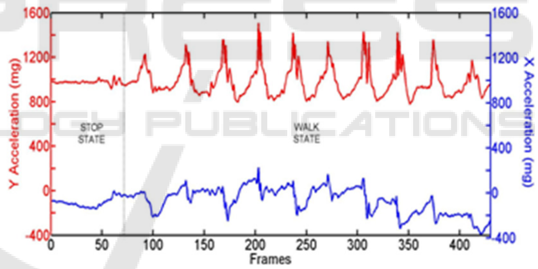

Figure 2: Typical curves of raw data of Ay (upper curve) and Ax (lower curve) during a regular walk and in the stop state.

In the case of Fig.2, the person was first in a stop state, then he started walking and made 10 steps. In the walk state, 10 peaks of acceleration can be clearly distinguished. We need to implement an algorithm able to recognize the movement disorders typical of PD: block, the regular steps, the irregular and short steps, the trunk oscillations. Hereafter, the results obtained with an artificial neural network (ANN) will be discussed, since other algorithms revealed less satisfactorily. We used an ANN with two layers (the hidden and the output layer). The network consists of 10 neurons, with a sigmoid weight function, connected in a feedforward topology. We used the 80% of the data for the training with a scaled conjugate gradient backpropagation algorithm already implemented in Matlab (C.M. Bishop et al., 1995), (T. Chau, 2001). The remaining 20% of the data was used to validate the algorithm. The cross entropy is chosen as performance function (D. Kline and V. Berardi, 2005). Ten epochs are sufficient to train the ANN in any studied case (discussed in the following), which indicates that the algorithm is very light and fast.

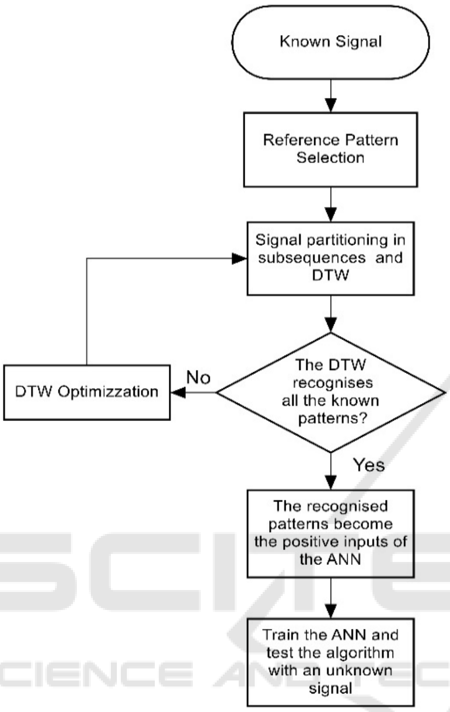

Figure 3: Flow diagram of the DTW-ANN training procedure.

Training: The flow diagram of training is reported in Fig.3. First of all, we choose the Ay signal containing a known number of reference patterns with a known size relative to steps, and we pick out a reference pattern from it. An example of a step reference pattern is shown in Fig.4a (selected in region II of Fig.2).

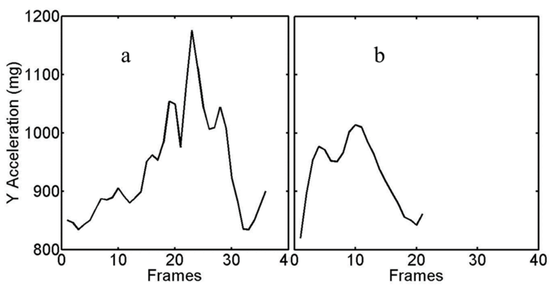

Figure 4: (a) Reference pattern associated to a regular step. (b) Reference pattern associated to a short step.

Apart from the amplitude, the reference pattern is characterized by the size (number of frames) related to the step time. The known signal is partitioned in sub-sequences having the same size of the reference pattern and the reference pattern is compared with the sub-sequences. To improve flexibility, the Dynamic Time Warping (DTW) technique is used, since it allows comparing similar patterns rather than just one specific pattern in the time subsequence (K.Wang et al., 1997). DTW is a nonlinear time normalization technique based on dynamic programming. Given two time series of different duration, a cost function can be calculated (E. Keogh and C. A. Ratanamahatana, 2005). A threshold of the cost function is set, which determines the degree of similarity between the reference signal and the specific subsequence. An example of the cost function of the DTW is shown in Fig.5. When the DTW recognizes the reference pattern in a sub-sequence then the corresponding ANN input is positive. On the contrary, if the known steps are not all recognized, the size of the reference pattern and/or the threshold of the cost function are changed (DTW optimization) and the DTW is run again.

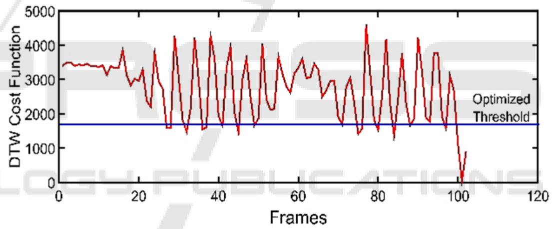

Figure 5: Cost function of the DTW and optimized threshold.

2.2 Experimental Results

The ANN is now tested using unknown signals. First, we monitored four young persons (all male) with temporary orthopedics problems in deambulation (defined “healthy”, in comparison with PD patients) who made the following exercise: stop, walk a few steps, turning, walk back, stop. The tests regarded the detection of regular steps, the irregular gait with step shortening (during turning), the trunk fluctuations. At a second stage, we monitored PD patients who made exactly the same exercise.

2.2.1 First Test on Healthy Persons: Regular Steps and Block

The raw Ay signal of an unknown walk is plotted in Fig.6 (upper red curve). Four intervals can be distinguished: interval I is intuitively associated to a stop state (the Ay value keeps constant at 1000 mg), intervals II and IV are clearly associated to a periodic movement, interval III refers to an irregular gait with short steps (while turning). The ANN was trained to recognize the stop state. The reference signal in this case was selected in interval I (it was an almost straight line, not shown for brevity) and the result is the lower dotted (ciano) curve. As expected, the ANN output is 1 in the I interval, is 0 during intervals II and III and assumes values between 0 and 1in the IV state, as whether short steps were present. The presence of regular steps was investigated using the reference pattern of Fig.4a. The outputs of the ANN in this case are shown in Fig.6 with the lower (blue) curve (ANN out-puts close to 1). As one can see, nine steps were recognized in region II and nine steps in region IV. No regular steps were identified in region III. We can conclude that interval III was recognized as a not walk state and a not stop state. The irregular steps need further investigation, and are the next focus.

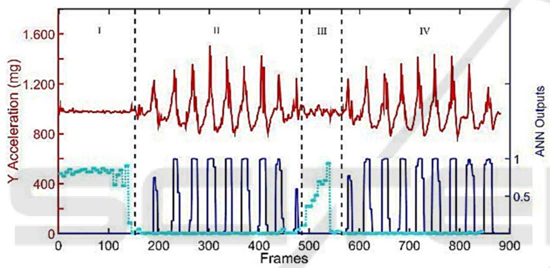

Figure 6: Raw Ay signal of the first unknown test signal (upper red curve) composed by stop state and walk state. ANN output associated to stop (ciano) and to walk (blue).

2.2.2 Second Test on Healthy Persons: Short Steps

The second unknown Ay signal is shown in Fig.7 (upper red curve). In this case, the exercise was focused on the step shortening. Here, the ANN had to recognize short steps and distinguish them from regular ones. Fig.4a, outlines different shapes, amplitudes, sizes). Therefore, in this experiment the ANN was trained using a reference pattern selected in region III. The new reference pattern is displayed in Fig.4b with arbitrary origin. The ANN outputs are shown in Fig.7. Although steps were irregular and featured variable length, the ANN recognized the short steps in interval III, where just one of the fifteen was regarded as uncertain (step # 10). Furthermore, a couple of irregular steps were also detected, when passing from region I to region II and from region II to region III.

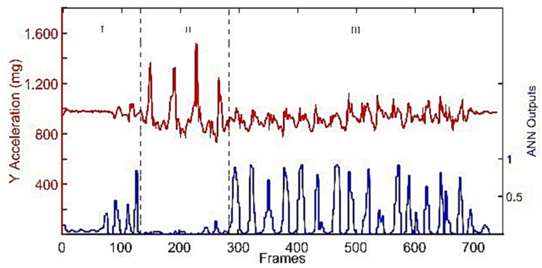

Figure 7: Raw Ay signal of the second unknown test signal (upper curve) composed by stop, walk state and irregular short steps. ANN output associated to the irregular short steps (lower curve).

2.2.3 Third Test on Healthy Persons: Trunk Oscillations

In this test, the ANN had to recognize trunk fluctuations in the x-y plane (referring to Fig.1b). In this experiment, legs were motionless and only the trunk oscillated pivoting on the pelvis. This situations is of particular interest because during a freezing of gait PD patients feel that their feet are stuck to the ground and they try repeatedly to make a step thrusting out and overbalancing. This is clearly associated to an increased risk of fall. In this case, the fact that the sensor is positioned on the head guarantees the maxi-mum sensitivity to the movement. In this experiment, the angle respect to the vertical axis varied in the range ±20 degrees. Again, the Ay raw signal was analysed and the curve is shown in Fig.8 (upper red curve). As expected, the trunk oscillations are very well characterized (region III). Regions I and II are associated, respectively, to a stop state and a walk state. The ANN was trained to recognize trunk fluctuations using a reference pattern selected in region III. It is shown in the inset. The ANN outputs are displayed in Fig.8 (lower blue curve). Recognition was excellent and all the trunk oscillations yielded ANN = 1.

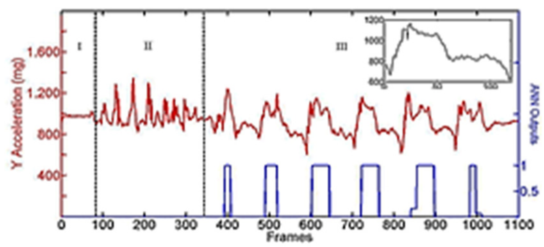

Figure 8: Raw Ay signal of the third unknown test signal (upper curve) composed by stop state, walk state and trunk oscillations. ANN output associated to the trunk oscillations (lower curve).

2.2.4 Test on PD Patients

All the results of the tests discussed above revealed that the headset system recognizes successfully the gait features and the trunk (and head) movements of healthy persons with temporary orthopedic problems.

Then, we started monitoring PD patients, but we limited to just a few (male, over 70) since results were not satisfactorily. Patients were asked to make the exercise described before. Tests were registered by a camera and supervised by doctors in order to establish the exact starting and ending time of the eventual FOG event. As an example, Fig.9 reports results relative to one of the PD patients experiencing a FOG during the test. The patient made four regular steps and a fifth short step, very close to the previous one. This fifth step defines an incipient FOG (pre-freezing state). Then the FOG event occurred, during which the patient made some irregular movements of the whole body, without making steps. The five steps are outlined with arrows on the Ay curve sketched in the figure. Looking at the ANN output, the first three steps are correctly detected, step 4 and step 5 are false negative, whereas a false positive is present during the FOG state, probably confusing a large movement of the body with a step. We can conclude that the headset is not similarly effective on PD patients as on healthy persons. This is due to the fact that PD patients feature a great variety of postural problems and irregular movements in many sections of the body, all mixed together. The headset device suffers from the presence of a joint (the neck) which can mix (or hide part of) the signals, making the information extremely "noisy" and confused, thus introducing false positive and false negative outputs.

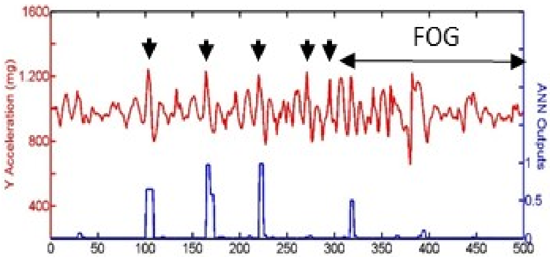

Figure 9: Raw Ay signal of the test signal taken on a PD patient (upper curve) composed by four regular steps, one short step close to the forth one, a FOG during which the body makes oscillations. The ANN reveals false negative and false positive outputs.

3 THE SENSING SYSTEM ON THE SHINS

In order to monitor movement disorders specifically in PD patients we designed another system with sensors positioned on the shins. In this case, the recognition algorithm is based on a time domain analysis of the sensor signals. The raw signals of accelerometers and gyroscopes are fused together through the attitude and heading reference system (AHRS) and the Madgwick's algorithm (β=0.15) (Madgwick et al., 2011). The data reading frequency from the sensor is 60Hz, which allows a correct sampling of the signal during FOG events since the relevant spectrum of FOG is 3 – 10 Hz. A quaternion based representation of the limb orientation and position is calculated. The angles α_{right} and α_{left} between the vertical axis and the right/left shin are sketched in Fig.10.

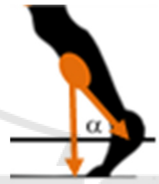

Figure 10: Angle between the vertical axis and the shin.

The angular velocities ω_{right}, ω_{left} obtained after angle derivation are used as the input for the FOG detection. A new algorithm was developed which calculates the low-pass of the angular velocities:

$$k_{right} = \text{lowpass}(|\omega_{right}|) \quad (1)$$

$$k_{Left} = \text{lowpass}(|\omega_{Left}|) \quad (2)$$

and introduces an index K = k_{right} + k_{left}. The algorithm in eqs.(1) and (2) is an improvement of a very recent algorithm proposed in literature (Y. Kwon et al., 2014), which uses the root mean square of the accelerometer signal of a single sensor and does not perform fusion with the gyroscope signal. Actually, thanks to the fusion of gyroscope and accelerometer signals, our algorithm allows to achieve a higher precision. This is paid in terms of the number of calculations, but the low pass filtering in the equations above needs a lower number and a lower rate of accesses to the microcontroller memory, respect to the root mean square method. As a matter of fact, we tested both algorithms and the proposed one exhibited better performance in terms of precision, with comparable calculation time.

A population of sixteen patients of different age and sex, at different stages of the disease was asked to wear the two sensors and make an exercise several times. The population is described in Table I. The exercise was: walking some steps, passing through an open door, turning and going back.

Table 1: Sex, age, disease stage of monitored patients.

male/female	under/over 65	early/advanced
9/7	5/11	6/10

FOG events occurred frequently during the exercises, especially when passing through the open door and during turning. In order to classify properly the states, a preliminary calibration of the system was performed. To this aim, the whole exercise was filmed with a camera and the sensor signals were recorded. The films were studied by doctors, who indicated the exact timing of the freezing events. Then, the calculated K curves were compared with the clinical observations by the doctors. This allowed defining three threshold values of K (T1-3) which classify the four states: regular gait (K>T3), pre-post freezing-state (T3>K >T2), involuntary freezing state (T2>K>T1) and voluntary rest state (K<T1). It is worth noticing that the values of T1-3 are the same for all the patients. From clinical side, distinguishing the involuntary freezing state from the rest state is crucial, and, fortunately, it relatively simple using inertial sensors since in the involuntary freezing state the muscle activity is always present and gives rise to lots of small movements which are clearly detected by the sensors. An example of α, ω and K is shown in the diagrams of Fig.11. Clinical report by the doctor about the exact FOG timing is sketched in the bottom diagram. The comparison between the K curve and the clinical reports allowed defining the T thresholds and the four classified states. In the example of Fig.11, a few FOG and pre-FOG events were identified by both doctors and the system. In one case (time=23-28s), the system distinguished between pre-FOG and FOG states, whereas doctors reported just a FOG in the whole time interval. Values of $T_{1\text{-}3}$ remained the same along all the measurements. Subsequent cross checks outlined an excellent agreement between the doctors reports and the automatic recognition of FOG performed by our system. An extremely low number of errors (false positive or false negative) were found. The particular algorithm implemented allowed to get the best performance published to date in terms of sensitivity, precision, accuracy and specificity. The average results on about two hours recording time and sixteen patients are shown in Table 2. As a comparison with the state of art, another system using inertial sensors positioned on the ankles featured a sensitivity of 77 % and a specificity of 86.5 % (S. Mazilu et al., 2013). This result was obtained on a population of fourteen PD patients.

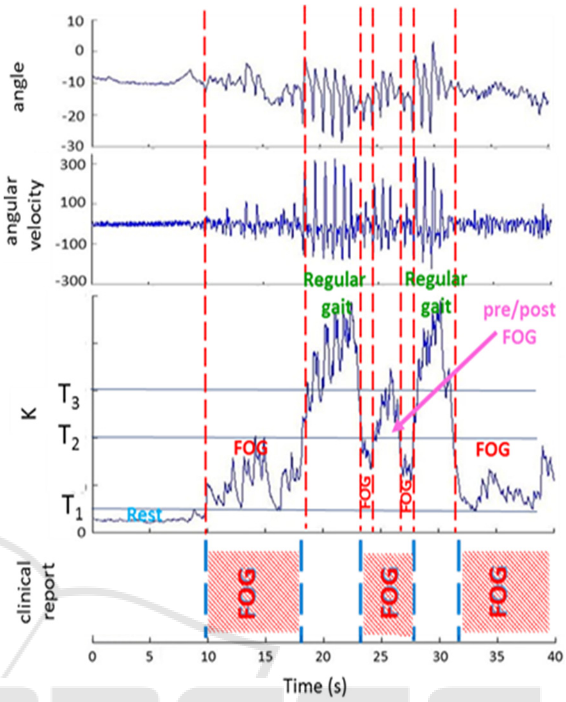

Figure 11: An example of angle and angular velocity measured by the sensor on the shin during the exercise. The calculate K index is also displayed. The bottom diagram reports the clinical observation of the FOG events timing.

Table 2: Performance of the system.

Sensitivity	Specificity	Precision	Accuracy
94.5%	96.7%	93.8%	95.6%

4 CONCLUSIONS

In this paper we proposed the realization of two wearable wireless sensing systems based on silicon integrated micro-electro-mechanical inertial sensors able to recognize in real time specific kinetic features associated to human motion disorders. The system is designed specifically for the Parkinson’s disease and gives an auditory stimulation to the patient to release block states in the freezing of gait. One system has the sensors in a headset, while the other one has sensors on the shins. They can be used at home or outdoor, during the daily activity of the patient. The hardware used for the two solutions is the same and uses the same integrated sensors. On the contrary, different algorithms were implemented in the two cases, accounting for the distinct peculiarities of the two solutions. In the case of the headset, a number of different algorithms were used in order to improve recognition of the gait features. In the paper, we discussed results regarding the recognition of the block state, regular and irregular steps, trunk oscillations obtained with an artificial neural network. For the system with sensors on the shins we used an algorithm filtering and processing in real time the angular velocities of the two legs. This gives excellent recognition of the irregularities of each step and detects even barely perceptible tremors in all the monitored PD patients, allowing distinguishing doubtless between the voluntary stop state and the involuntary block due to the FOG. Further optimization and simplification of the detection algorithm can be achieved by better manipulating the quaternions representation of the limbs.

The headset has advantages in terms emphasized sensitivity to trunk oscillations, easy wearability and direct auditory feedback. This implies an excellent detection of specific typologies of motion disorders, and makes the system compact and energy efficient since gives the audio-feedback without any wired/wireless connection. Unfortunately, PD patients feature a great variety of postural problems and irregular movements in all the sections of the body, and the system suffers from the presence of a joint (the neck) which can mix (or hide part of) the signals, making the information extremely "noisy" and confused, thus introducing false positive and false negative outputs. For this reason, the headset can be better employed for other types of motion disorders, as in the case of temporary orthopedics ones.

The other device requires an additional device in the ear for the audio-feedback, but guarantees the best performances presented in literature to date in terms of sensitivity, specificity, precision and accuracy in the detection of the FOG events. The system was validated on a population of sixteen patients of different age, sex and stage of the disease.

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